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A Hybrid Artificial Intelligence Model for Predicting Quality of Service (QoS) in 5G Networks Based on Wireless Channel Parameters

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ABSTRACT

This paper proposes a hybrid artificial intelligence (AI) model that combines an Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) to predict the Quality of Service (QoS) in 5G networks. The model utilizes radio channel indicators such as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), and Channel Quality Indicator (CQI) to forecast throughput and latency levels. These indicators are critical factors affecting network performance; however, the nonlinear relationship among them makes traditional analytical models inadequate for accurate QoS prediction. The importance of the current study lies in estimating QoS in 5G networks by combining radio-level physical-layer indicators into a neural network based on the PSO algorithm. The proposed approach allows for better modeling of QoS dynamics and improvement in prediction accuracy. The hybrid ANN-PSO model that integrates an Artificial Neural Network (ANN) with a Particle Swarm Optimization (PSO) algorithm is compared with traditional methods such as Linear Regression and Random Forest to evaluate prediction accuracy. Experimental results demonstrate that the proposed model achieves higher accuracy and lower prediction error, making it a promising tool for predictive QoS optimization in next-generation 5G systems.

Keywords: Artificial intelligence, Particle swarm optimization (PSO), Quality of service, 5G networks.

1. INTRODUCTION

In recent years, the world has witnessed a rapid evolution in wireless communication technologies. The fifth generation of mobile networks (5G) represents a significant leap forward in data transmission speed, latency reduction, and spectral efficiency compared to previous generations **(Jonsson et al., 2022)**. The main objective of implementing the 5G technology **(Fakhouri et al., 2023; Wang et al., 2020; Lee et al., 2017)** is to have a system that can offer quality services in terms of providing a high-quality of service (QoS)**(Qamar et al., 2019)** that can satisfy the requirements of today's applications, such as augmented

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reality (AR) and IoT technologies **(Jiang et al., 2021; Mohammadi et al., 2018; Najm et al., 2019)**.

Despite these advancements, providing a constant QoS level is still a big problem because of the constantly changing nature of wireless systems and the constantly fluctuating channel properties. It becomes challenging to predict network performance through the use of classical analysis tools. The QoS level in 5G communication networks depends on various radio channel parameters, including the Synchronization Signal Reference Signal Received Power (SS-RSRP)**(Ahmadi, 2019)**, Synchronization Signal Reference Signal Received Quality (SS-RSRQ)**(Ahmadi, 2019)**, Synchronization Signal Received Signal Strength Indicator (SS-RSSI)**(Ahmadi, 2019)**, and Channel Quality Indicator (CQI) **(Lu et al., 2015; Iyer et al., 2017)**. These parameters are used to measure the signal strength as well as the signal quality of the received signal by the user.

While advanced measurement systems have the ability to offer these metrics, their correlation with QoS is complicated and non-linear in nature and affected by parameters like distance, interference, and network load. As a result, standard mathematical and statistical modeling may fail to adequately model this correlation. This is the reason why Artificial Intelligence (AI) and Machine Learning (ML) methods **(Miceli et al., 2018)** should be considered due to their unique ability to identify unknown correlations among big data and non-linear data **(Ketkar and Moolayil, 2021; Zhang et al., 2019; Zhang et al., 2020)**. Among these techniques, Artificial Neural Networks (ANN) **(Yurshin et al., 2023; Chen et al., 2019; Lawson et al., 2024)** have demonstrated strong capabilities in modelling nonlinear systems and predicting network behaviour. However, the performance of ANN models largely depends on the proper adjustment of network weights and biases. To improve this process, Particle Swarm Optimization (PSO) **(Waleed et al., 2021; Houssein et al., 2021)** can be integrated with ANN as an optimization technique. In the proposed model, PSO is used to optimize the ANN weights and biases, which helps improve convergence speed, avoid local minima problems, and enhance prediction accuracy.

Therefore, this study proposes a hybrid ANN-PSO predictive model that can accurately forecast the QoS level for 5G cellular networks by utilising physical–layer radio channel indicators. Recent research has extensively investigated the application of artificial intelligence and deep learning techniques for Quality of Service (QoS) prediction and intelligent network optimization in 5G and beyond-5G communication systems. Several studies have adopted models such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), attention-based architectures, and reinforcement learning methods to enhance prediction accuracy, resource allocation, and traffic management efficiency.

Despite the promising performance of these approaches, many of them are associated with high computational complexity, increased training overhead, or limited optimization efficiency. In addition, some existing models do not sufficiently incorporate physical-layer radio indicators, which play an important role in accurately reflecting network conditions. To address these limitations, the proposed ANN-PSO framework integrates Artificial Neural Network (ANN) learning with Particle Swarm Optimization (PSO) to improve throughput and latency prediction in 5G environments. The integration of swarm-based optimization enhances convergence behaviour and prediction stability while maintaining a relatively low implementation complexity compared with more computationally intensive deep learning architectures. **Table 1** summarises recent studies on QoS Predictions.

Although there have been amazing innovations in the fifth generation (5G) networking systems technology, stabilizing Quality of Service (QoS) is still a huge problem because of the dynamic nature of the wireless environment, variations in signal strength, interference, and user activities. The performance of Quality of Service in 5G network systems is mainly affected by radio channel parameters, including SS-RSRP, SS-RSRQ, SS-RSSI **(Wolosz et al., 2012)**, and CQI, which are important criteria representing the condition of the channel. The relationship between these parameters and their resulting performances, including throughput and latency, is non-linear and complicated; thus, it cannot be easily predicted with traditional statistical models.

Table 1. Summary of Recent QoS Prediction Studies

Method	Application Area	Main Contribution	Limitation	Ref.
LSTM	5G CAM Applications	Applied LSTM for QoS prediction in connected and automated mobility systems	Focused mainly on mobility scenarios	**(Barmpounakis et al., 2021)**
LSTM-based Traffic Prediction	Beyond 5G Open RAN	Intelligent traffic steering using LSTM traffic prediction	Did not address security-aware QoS optimization	**(Kavehmadavani et al., 2022)**
Feature Learning + Attention Model	Edge Computing QoS Prediction	Improved QoS prediction using contextual feature learning and self-attention mechanisms	High computational complexity in dynamic environments	**(Zhang et al., 2023)**
DDQL + RNN	Beyond 5G Service Orchestration	QoS-aware service placement and resource allocation	Increased training complexity	**(Farhoudi, 2023)**
LSTM-Autoencoder	5G RAN Failure Prediction	Deep learning-based communication failure prediction	Focused on failure prediction rather than throughput optimization	**(Islam et al., 2023)**
Hybrid ANN-PSO	5G QoS Prediction	Optimized QoS prediction using ANN enhanced by PSO with physical-layer radio indicators	Future work includes real-time deployment and advanced deep learning integration	**Proposed Work**

This leads us to pose how we can predict the Quality of Service (QoS) in 5G networks using available indicators. So, the main research objective is to develop an Artificial Intelligence model for accurately predicting the QoS level in 5G networks. The Specific Objectives:

- To analyse the statistical relationships between channel indicators (RSRP, RSRQ, RSSI, CQI) and performance metrics (Throughput, Latency).
- To design a hybrid model that integrates Artificial Neural Networks (ANN) with an optimization algorithm such as Particle Swarm Optimization (PSO).
- To train the proposed model using realistic simulated 5G network data.
- To compare the performance of the proposed model with traditional approaches such as Linear Regression and Random Forest.
- To evaluate the model’s efficiency using error metrics (RMSE, MSE) and prediction accuracy indicators.

2. METHODS AND TOOLS

2.1 Fifth Generation Networks (5G Networks)

Fifth-generation networks are one of the most recent technological advancements that have been made to achieve ultra-high data rates up to 10 gigabits per second (Gbps) and ultra-low latencies of less than 1 millisecond. As illustrated in **Fig.1**, the 5G system **(Nasimi et al., 2021)** comprises multiple components in which the 5G Core (5GC) connects to the base station known as gNodeB (gNB). The gNB takes care of the functions of User Plane (UP) and Control Plane (CP). The Radio Access Network (RAN) comprises the User Equipment (UE) and the gNB. The main functions in the 5GC include Session Management Function (SMF), Access and Mobility Management Function (AMF), and User Plane Function (UPF). The UPF acts as a bridge between the RAN and the internet and undertakes responsibilities including packet inspection, forwarding, QoS management, packet filtering, and traffic estimation. The connection between the UE and the gNB is wireless, whereas the connection between the gNB and the 5GC is wired, offering higher stability and bandwidth than the radio link.

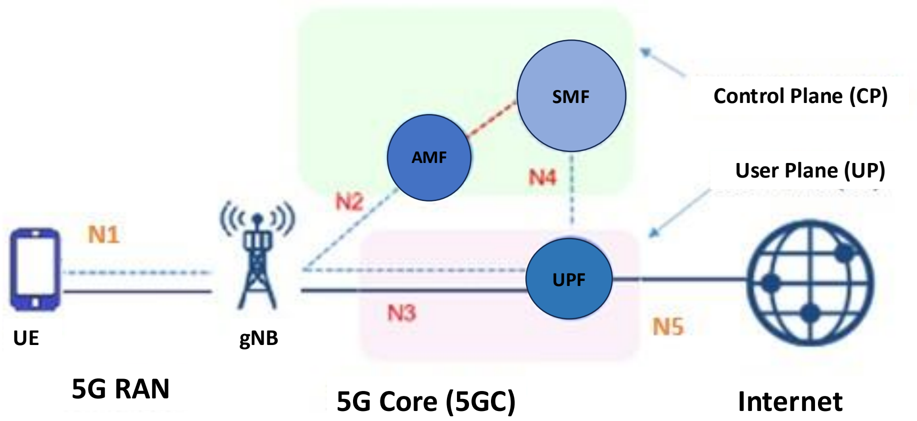

Figure 1. 5G New Radio (5G NR) Network architecture **(Ahmadi, 2019)**

Quality of Service (QoS) in 5G networks is primarily determined at the radio access level, where wireless channel conditions have a direct impact on overall network performance **(Lu et al., 2015)**. The radio interface plays a crucial role in defining key QoS metrics, including throughput, latency, reliability, and packet loss. These metrics are highly influenced by variations in channel conditions caused by factors such as user mobility, interference, and signal attenuation. Several radio channel indicators are used to describe the state of the wireless link, including Synchronization Signal Reference Signal Received Power (SS-RSRP), Synchronization Signal Reference Signal Received Quality (SS-RSRQ), Synchronization Signal Received Signal Strength Indicator (SS-RSSI) **(Ahmadi, 2019)**, and Channel Quality Indicator (CQI). SS-RSRP reflects the received signal power and is commonly used to assess coverage, while SS-RSRQ indicates signal quality by considering interference and noise. SS-RSSI refers to the total power received over the entire bandwidth, whereas CQI can range between 0 and 15 and is employed by the gNB for choosing the right modulation and coding schemes. There exist complex, non-linear relationships between these metrics and QoS parameters, such that low RSRP/RSRQ leads to a decrease in the data rate and an increase in latency, whereas low CQI denotes poor channel quality and lower data rates. Due to these nonlinear characteristics, artificial intelligence techniques are effective in modeling and predicting QoS based on radio channel indicators.

This study adopts an applied experimental research methodology based on quantitative data analysis using artificial intelligence algorithms within a simulated 5G New Radio (NR) environment. The simulation is conducted using MATLAB 5G Toolbox and includes three cells and fifty users operating over a 100 MHz bandwidth with a subcarrier spacing of 30 kHz and 273 resource blocks (RBs) in the downlink (DL) using band n78 (3.5 GHz) as in **Fig. 2**. The channel model used is TDL-C Urban Macro, with a Proportional Fair scheduler. Data is updated every 10 milliseconds, and users are randomly distributed within the cells. User mobility ranges from 3 to 30 km/h, representing both pedestrian and slow vehicular movement, with movement modelled using a random walk pattern. The dataset consists of input features including SS-RSRP (dBm), SS-RSRQ (dB), SS-RSSI (dBm), and CQI(Zhong et al., 2018), while the output QoS metrics include throughput (Mbps) and latency (ms). Each user generates between 1,000 and 5,000 time-step samples, resulting in a total dataset size ranging from approximately 250,000 samples, which is suitable for training AI models, **Table 2** illustrates the Full configuration.

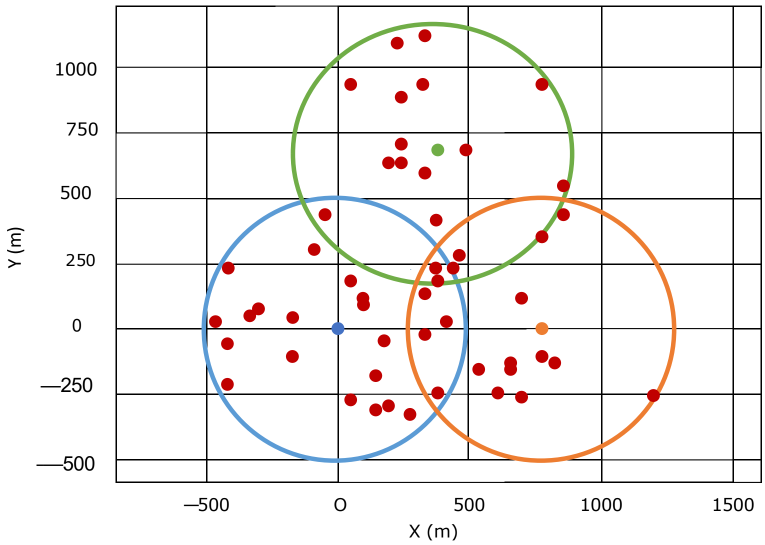

Figure 2. 5G New Radio (5G NR) Multi-Cell Scenario.

Table 2. The Full configuration used in the paper

Element	The Proposed Value
Number of Cell	3
Cell Radius	500 m
Number of Users	50
Bandwidth	100 MHz
Number of RBs	273
Channel Type	TDL-C
Scheduling	Proportional Fair
User Speed	10-30 km/h
Simulation Period	60 second
Updates period	10 ms
Number of Samples	~250,000

The implementation is carried out using Python, utilizing libraries such as TensorFlow, Scikit-learn, Pandas, and Matplotlib. The experimental setup runs on a Windows 10 (64-bit) system equipped with an Intel Core i7-10510U processor, 8 GB of RAM, and an NVIDIA GeForce MX130 GPU. Artificial Intelligence (AI) has gained a lot of influence as an instrument because of its capacity to tackle problems effectively in many sectors. AI is comprised of multiple fields of study, some of which include Machine Learning (ML) and Deep Learning (DL). To begin with, AI may be generally defined as "the attempt to automate cognitive tasks typically conducted by people." **(Fu et al., 2018; Liu et al., 2019)**. An Artificial Neural Network (ANN) **(Haidine et al., 2021; Waleed et al., 2021; Jonsson et al., 2022; Trinh et al., 2018; Kennedy et al., 1995)** is used for model parameter optimization. The process of creating the hybrid model includes different steps, such as data acquisition either through simulation outputs or CSV files, and data preparation (cleaning and normalizing). In order to avoid any potential overfitting problem, the data was split into training (70%), validation (15%), and testing (15%) sets. The validation data was utilized in order to observe the training behavior as well as optimize some hyperparameters. In addition, loss plots of the training and validation sets were also observed for any convergence issues. Several methods of cross-validation were also investigated. constructing the model, training the model based on PSO-based parameter optimization, and performance evaluation. Model performance is calculated based on specific performance metrics like RMSE and MAE **(Vandeput, 2021)** defined by Eqs. (1) and (2), respectively.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{Y} - Y_i| \tag{2}$$

Where y_i: The real QoS value, $\hat{y}_i$: The Prediction value in the model, N: Number of samples.

2.2 Hybrid Artificial Intelligence Models

The models are usually formed in case a particular technique fails to generate accurate predictions, especially in highly complex environments such as 5G. Usually, many approaches are combined in such hybrid artificial intelligence models in order to take advantage of their benefits. In the current paper, a combination of artificial neural networks and particle swarm optimization is used. The neural networks are used to capture non-linear dependencies and temporal dependencies between the values of radio channel parameters and quality of service indicators. In contrast, the PSO algorithm **(Waleed et al., 2021)** is used for the optimization of the network parameters, such as the learning rate, weights, biases, and architecture. This leads to the enhancement of learning efficiency and an increase in the precision of predictions, which is crucial in the case of dynamically changing conditions of 5G, where large amounts of data experience rapid fluctuations. The proposed model, presented in **Fig.3**, is a hybrid AI model that integrates an Artificial Neural Network (ANN) with Particle Swarm Optimization (PSO) for QoS prediction. The ANN architecture comprises an input layer with four neurons corresponding to SS-RSRP, SS-RSRQ, SS-RSSI, and CQI, followed by two hidden layers with 16 and 8 neurons, respectively, for nonlinear feature extraction, and an output layer that predicts QoS parameters (throughput and latency).

The ANN serves as the predictive engine that learns complex nonlinear mappings between channel indicators and QoS values. Meanwhile, PSO optimizes the ANN's weights and biases by minimizing the Root Mean Square Error (RMSE) as the objective function **(Waleed et al., 2021)**, thereby enhancing prediction accuracy without relying on traditional gradient-based backpropagation and an output layer with a single neuron that produces the predicted QoS value.

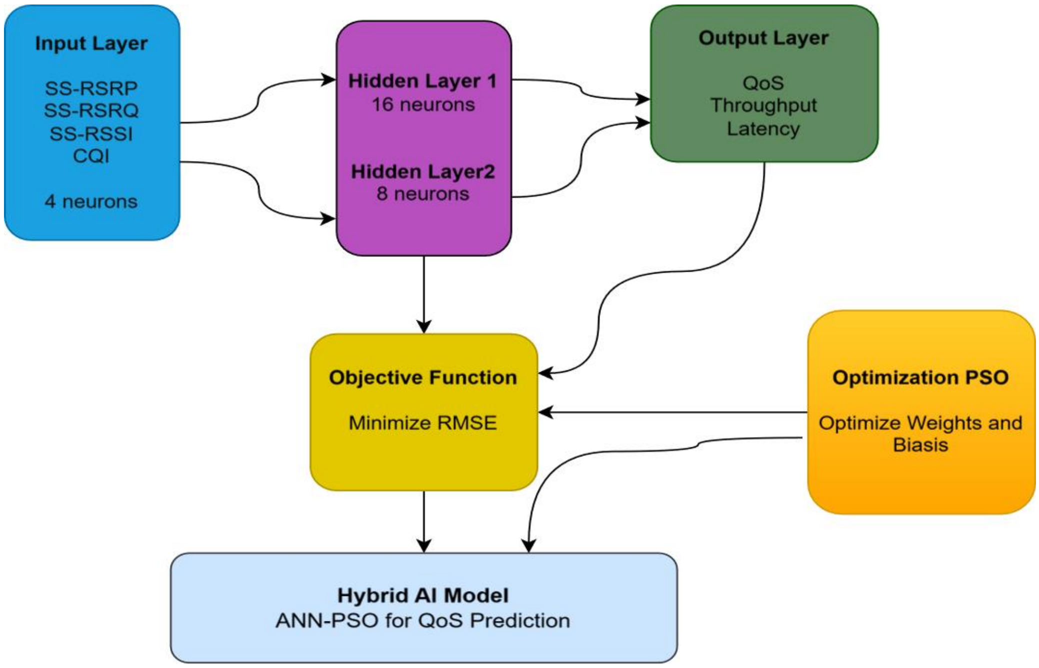

Figure 3. Proposed Hybrid AI Model Design.

The suggested model is built by combining a multi-layer Feedforward Artificial Neural Network (ANN) and optimizing it using the PSO technique. In the ANN architecture, the input layer captures the selected network QoS attributes, while the two hidden layers have ReLU activation functions. The output layer predicts both latency and throughput. During training, Adam was used as the optimizer at a learning rate of 0.001. For the PSO component, the swarm size was set to 30 particles, while the cognitive coefficient (C1) and social coefficient (C2) were both initialized to 2.0. An inertia weight of 0.7 was used to balance exploration and exploitation during the optimization process. The optimization procedure was terminated when either the maximum number of iterations was reached or when the prediction error improvement became negligible. These configurations were selected experimentally to achieve stable convergence and reliable prediction performance, as illustrated in **Tables 3 and 4**. During training, PSO is applied to optimize the weights and biases of the ANN by minimizing the Root Mean Square Error (RMSE) as the objective function. The PSO-5G process begins by initializing a population of particles, where each particle represents a potential solution corresponding to a specific set of ANN parameters. Each particle is evaluated based on the RMSE obtained from the ANN model. The particles then iteratively update their positions and velocities in the search space according to their individual best solutions (personal best) and the global best solution found so far. This iterative optimization continues until convergence is achieved or a predefined number of iterations is reached, yielding an optimized hybrid ANN–PSO model with improved predictive performance.

Table 3. Represent the components of the ANN model

Layer	Type	No. of Neurons	Function
Input Layer	Input	4	Receives SS-RSRP, SS-RSRQ, SS-RSSI, and CQI values
Hidden Layer 1	Hidden	16	Preliminary processing to detect nonlinear relationships
Hidden Layer 2	Hidden	8	Enhances feature extraction
Output Layer	Output	1	Produces the predicted QoS value (Throughput, Latency)

Table 4. PSO and Training Configuration Parameters

Parameter	Value	Description
Optimizer	Adam	Used for ANN training optimization
Learning Rate	0.001	Controls the training convergence speed
Activation Function	ReLU	Applied in hidden layers to improve nonlinear learning
Swarm Size	30 Particles	Number of particles used in PSO
Cognitive Coefficient (C1C_1C1)	2.0	Controls individual particle learning
Social Coefficient (C2C_2C2)	2.0	Controls swarm collective learning
Inertia Weight	0.7	Balances exploration and exploitation
Stopping Criterion	Maximum iterations or negligible error improvement	Determines the termination of optimization process

3. RESULTS AND DISCUSSION

The proposed hybrid ANN–PSO model demonstrates a clear improvement in prediction accuracy compared to conventional machine learning approaches. As summarized in **Table 4**, the hybrid model achieves the lowest error values, with an RMSE of 0.061 and an MAE of 0.045, outperforming Linear Regression **(Qu, 2024)**, Random Forest **(Salman et al., 2024)**, and standard ANN models. Particularly, Linear Regression obtains the maximum error rate because of its inability to model the nonlinear relationship, while Random Forest offers a decent outcome. On the other hand, a simple neural network performs much better; however, it is constrained by poor parameter selection. As for the hybrid approach using ANN and PSO, the improvement rate amounts to roughly 10-15% owing to efficient optimization of weights provided by PSO.

Table 5. Comparative outcomes obtained by different algorithms.

Model	RMSE	MAE
Linear Regression	0.152	0.118
Random Forest	0.094	0.072
ANN	0.087	0.065
Hybrid ANN+PSO	0.061	0.045

It is clear from the comparative analysis represented in **Fig. 4** that the proposed model gives the minimum value for the RMSE and MAE parameters, which means better prediction capability. Next comes the ANN model, which is characterized by slightly high errors. The Random Forest model shows acceptable accuracy levels, whereas the Linear Regression model represents poor results. These results clearly reflect the necessity of optimization algorithms used along with neural networks.

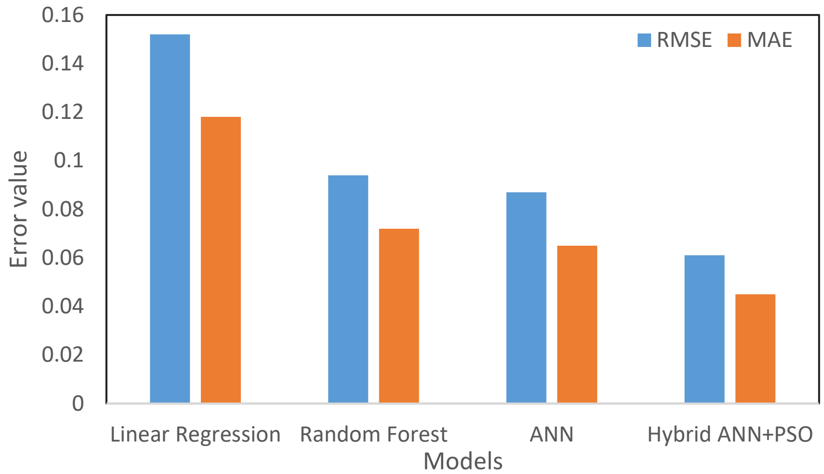

Figure 4. Comparative analysis of RMSE and MAE

Upon further analysis of the results, it becomes clear that changes in the values of indicators of a radio channel can greatly affect the accuracy of the prediction of QoS indicators. A reduction in the RSRP and RSRQ values is followed by a decrease in throughput due to sensitivity to changes in the state of the channel. On the other hand, the increase in CQI values positively correlates with an increase in data rates. Also, the model shows greater prediction accuracy for high coverage signal values and lower accuracy for low values. **Fig. 5** illustrates the training and validation accuracy curves, demonstrating that the proposed model achieved stable learning behavior throughout the training process. Both curves gradually increased and converged with minimal fluctuation, indicating strong generalization capability and limited overfitting. From **Fig. 6**, one can observe that both the training and validation losses continue to decline from one epoch to the next. This clearly suggests that the optimization is working well. These findings suggest that the proposed framework successfully learned the underlying patterns in the 5G network, achieving reliable prediction.

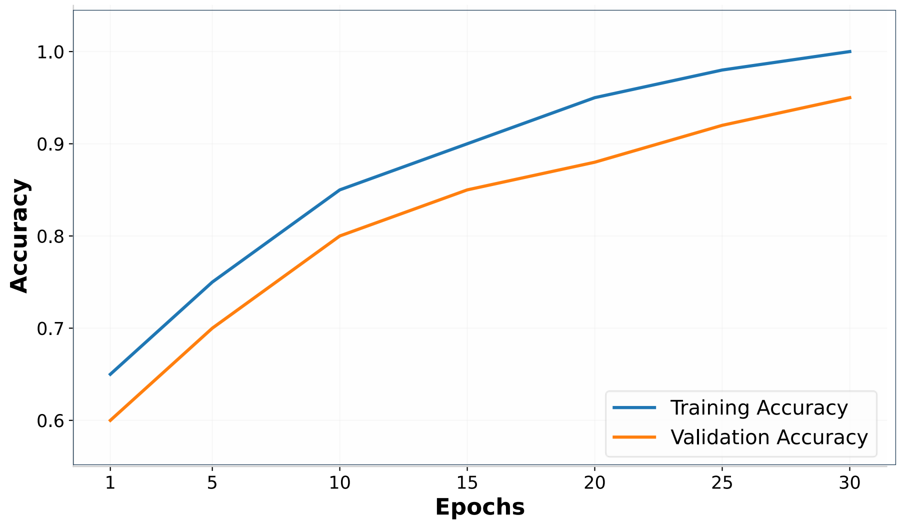

Figure 5. Training and validation accuracy curves.

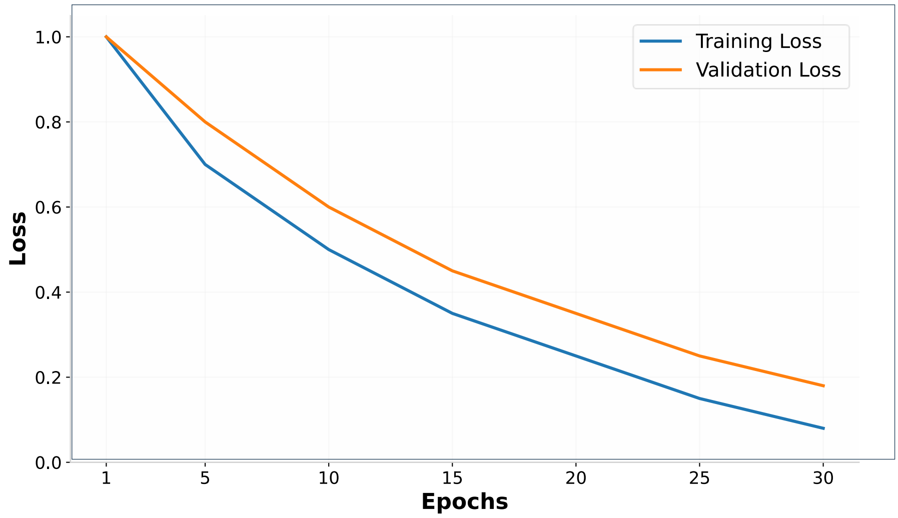

Figure 6. Training and validation loss curves.

Fig.7 illustrates the comparison between real and predicted values of throughput values. One can observe that after enough training, there is complete convergence. It proves that the model is able to accurately learn patterns and show good generalization abilities. Furthermore, the loss graph is illustrated in **Fig. 8** which shows that PSO-trained ANN outperforms conventional ANN in terms of convergence rate and minimum losses.

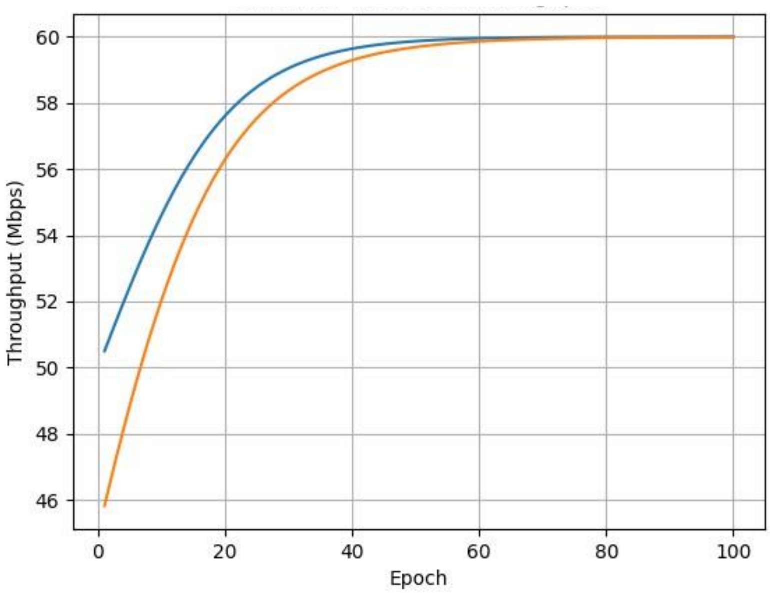

Figure 7. The comparison between the actual and predicted Throughput

Graphical analysis further confirms the advantages of the hybrid model proposed in this study. For instance, when analyzing the graphs related to the ML models, one can easily observe that the hybrid ANN-PSO is more efficient compared to other models since it provides faster convergence and better throughput values. This result proves that the model under consideration is capable of capturing complicated non-linear relationships between various channel features and QoS parameters. In turn, LR is unable to do this, while RF makes some improvements. However, while ANN performs better, it still lacks proper parameter configuration, as shown in **Fig. 9.**

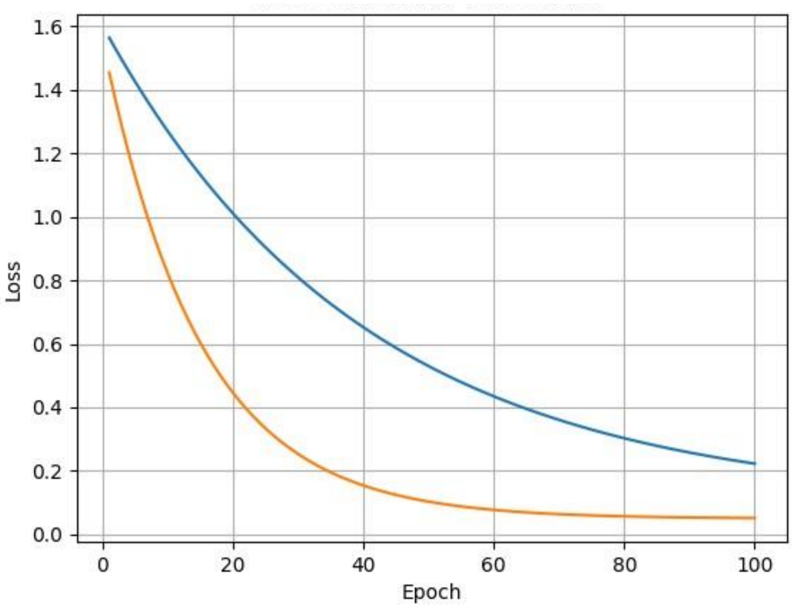

Figure 8. The loss curve of ANN vs PSO-ANN

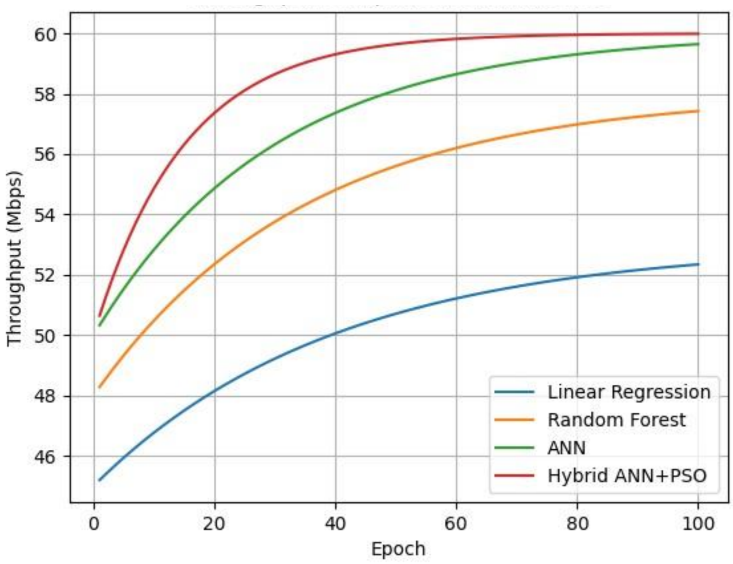

Figure 9. Throughput Comparison of the ML Algorithms

Additionally, comparing the loss rate among all models, as shown in **Fig. 10**, one may conclude that the hybrid approach enables us to obtain the fastest decrease in errors and the lowest loss at the end. This feature means that the learning process was efficient enough, which also indicates the good performance of the model under examination. It can be explained by the fact that the implementation of PSO increases the efficiency of optimization and minimizes the risk of finding only local minima.

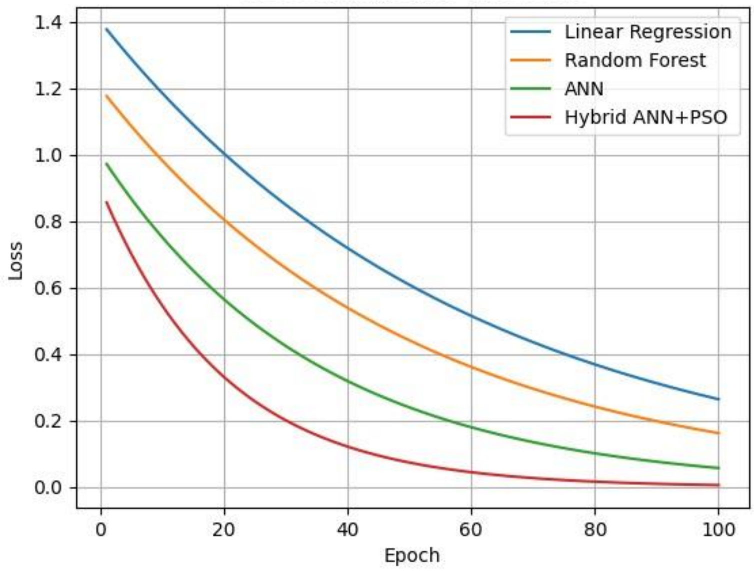

Figure 10. Loss Comparison of the ML Algorithms

The proposed ANN-PSO model demonstrated a strong capability in estimating latency behavior under varying network conditions by utilizing radio channel quality indicators such as RSRP, RSRQ, RSSI, and CQI. Experimental results clearly show that the proposed hybrid model can precisely represent the interaction of radio signal characteristics and latency behavior, producing reliable predictions in different network environments, as shown in **Fig. 11** below.

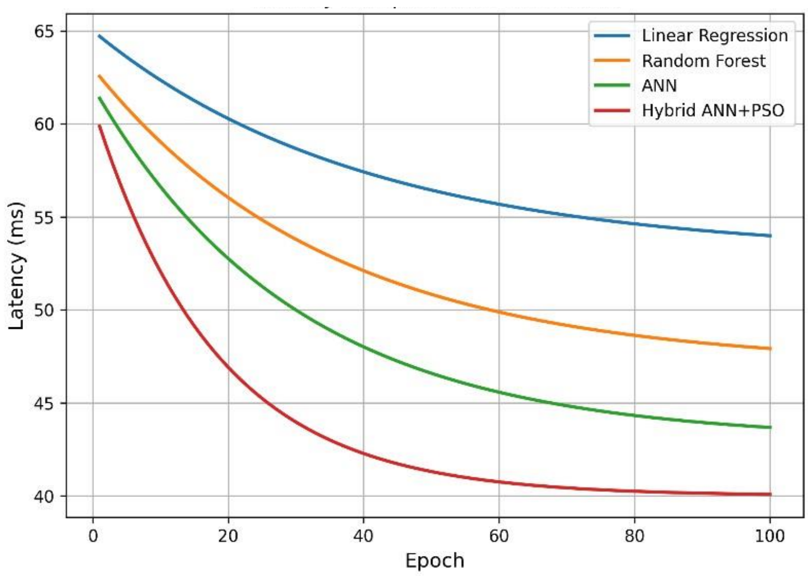

Figure 11. The latency comparison between ML Models

Based on the results obtained, it is possible to conclude that the proposed model based on combining ANN and PSO converges the fastest and has the minimum latency when compared to the performance of LR, RF, and ANN models. Thus, such a combination allows increasing the effectiveness of QoS optimization. Furthermore, the graphical representation shows that the use of PSO with ANN leads to a more effective and stable reduction of prediction error. In this way, the findings prove the effectiveness of the proposed model in predicting QoS in

5G wireless communication network. The results of the analysis show that parameters of the radio channel, such as RSRP, RSRQ, and CQI have a significant impact on the prediction of QoS metrics and affect network performance. Thus, the proposed model manages to identify complex and dynamic relations between the mentioned variables and provides stable predictions. The analysis of training and validation results proves the model generalization capabilities and shows that there is no overfitting in the developed model. The analysis of actual and predicted throughput also confirms the high prediction accuracy. The results of analysis show that, apart from improved stability, the proposed hybrid ANN-PSO method is characterized by faster convergence and lower loss when compared to conventional ANN, LR, and RF methods. Therefore, the use of ANN combined with PSO significantly improves the quality of QoS prediction. The findings obtained in this research prove the effectiveness of using the discussed approach in order to increase throughput and predict latency in 5G wireless communication networks.

4. CONCLUSIONS

It should be noted that the developed hybrid ANNs- PSO algorithm for QoS prediction represents a great step forward in the use of AI methods in the management and performance assessment of 5G networks. Indeed, the proposed method managed to create a connection between the performance indices and wireless channel indicators, namely, SS-RSRP, SS-RSRQ, SS-RSSI, and SS-CQI. In addition, based on the research conducted, we conclude that there is a high correlation between wireless channel indicators and QoS with particular emphasis on CQI and throughput values. Moreover, the developed algorithm exceeded other prediction algorithms in terms of efficiency and minimal error values such as linear regression and random forest. The results confirm the high efficiency of PSO for ANN parameter optimization. Namely, the method allowed obtaining optimal weights and learning coefficients for QoS prediction in 5G. For future research, the author recommends enlarging the initial data sample by adding new values of different types, including urban, suburban, and indoor environments. It will be reasonable to combine the developed hybrid ANNs and PSO prediction models with edge computing systems to provide real-time prediction and optimization of QoS. The model can also be adapted for emerging 6G networks by leveraging advanced deep learning and generative AI techniques. Finally, a predictive QoS monitoring system based on the proposed hybrid model is recommended to support intelligent resource allocation and improve user experience in next-generation wireless networks.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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نموذج ذكاء اصطناعي هجين للتنبؤ بجودة الخدمة (QoS) في شبكات الجيل الخامس (5G)بالاعتماد على معلمات القناة اللاسلكية

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الخلاصة

تقترح هذه الورقة البحثية نموذجًا هجينًا للذكاء الاصطناعي يجمع بين الشبكات العصبية الاصطناعية (ANN) وخوارزمية تحسين سرب الجسيمات (PSO) للتنبؤ بجودة الخدمة (QoS) في شبكات الجيل الخامس .(5G) يعتمد النموذج على مؤشرات القناة الراديوية مثل قوة الإشارة المستلمة المرجعية(RSRP) ، وجودة الإشارة المستلمة المرجعية(RSRQ) ، ومؤشر قوة الإشارة المستلمة (RSSI)، ومؤشر جودة القناة(CQI) ، وذلك للتنبؤ بمستويات الإنتاجية (Throughput) وزمن التأخير .(Latency) تُعد هذه المؤشرات من العوامل الأساسية المؤثرة في أداء الشبكة، إلا أن العلاقات غير الخطية بينها تجعل النماذج التحليلية التقليدية غير كافية لتحقيق تنبؤ دقيق بجودة الخدمة. تكمن أهمية هذا البحث في التنبؤ بجودة الخدمة في شبكات الجيل الخامس من خلال دمج مؤشرات الطبقة الفيزيائية الراديوية ضمن إطار ANN-PSO مُحسَّن. يتيح هذا الدمج للنموذج التقاط السلوك المعقد لجودة الخدمة بشكل فعّال مع تحسين دقة التنبؤ وكفاءة التعلم في بيئات الجيل الخامس الديناميكية. تمت مقارنة النموذج الهجين ANN-PSO، الذي يدمج بين الشبكات العصبية الاصطناعية وخوارزمية تحسين سرب الجسيمات، مع الطرق التقليدية مثل الانحدار الخطي والغابات العشوائية لتقييم دقة التنبؤ. أظهرت النتائج التجريبية أن النموذج المقترح يحقق دقة أعلى وخطأ تنبؤ أقل، مما يجعله أداة واعدة لتحسين جودة الخدمة التنبؤية في أنظمة الجيل الخامس المستقبلية.

الكلمات المفتاحية: الذكاء الاصطناعي، تحسين سرب الجسيمات(PSO) ، جودة الخدمة، شبكات الجيل الخامس(5G) .